REGULATING CONSUMER FINANCIAL PRODUCTS: EVIDENCE FROM CREDIT CARDS

Online Appendix

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A DATA APPENDIX

A.1 Constructing Revenue and Cost Measures

In our data, a number of important revenue and cost measures for credit cards are not observed at the account level, but only at the credit card portfolio level. These include the cost of funds, operational expenses, interchange income, rewards expenses, and fraud expenses. Since most of these measures broadly scale with either average daily balances (cost of funds, operational expenses) or purchase volume (interchange income, rewards, and fraud), we can use the information in the portfolio-level data to construct account-level measures of these variables. At the portfolio level, banks also report "daily average managed receivables," but not total monthly transaction volume.

A.1.1 Cost of Funds

The cost of funds is the interest rate paid by financial institutions for the funds that they deploy in their business. The cost of funds also varies across banks, depending, amongst other things, on their ability to raise funds in the interbank market. Banks report "total interest expense accrued for the month to fund credit card receivables" in the portfolio-level data. This allows us, for every bank and month, to calculate the annualized cost of funding one dollar of credit card lending. The top panel of Figure A.I shows the average of this cost of funds measure across banks. The cost of funds declined markedly over our sample period, with particularly steep drops in 2008, as the federal funds rate declined to zero. The graph also shows the 11th District Cost of Funds Index (COFI), a monthly weighted average of the interest rates paid on checking and savings accounts offered by financial institutions operating in the states of Arizona, California and Nevada. This index is widely seen as a measure of the refinancing costs of U.S. financial institutions. Reassuringly, it moves closely with the cost of funds derived from the credit card portfolio data. For every account, we calculate the cost of funding that account's receivables by multiplying the average daily balances with the cost of funds for the corresponding bank and month.

A.1.2 Operational Costs

At the portfolio level, we also observe banks reporting three other components of cost. These are *collection expenses*, which include the costs incurred to collect problem credit; *marketing / acquisition and card processing costs*, which include the costs to acquire, advertise, and promote and process credit cards; and *other expenses*, which include costs for servicing, cardholder billing, processing interchange, processing payments, card issuing, authorizations, card administration and outside services/outsourcing. We combine these three expense categories into the category "operational costs." For each month, we calculate the ratio of these operational costs to the average daily managed receivables. This ratio is shown in the middle panel of Figure A.I. We use the smoothed version of this series to assign a corresponding "operational cost" to every account by multiplying the average daily balances with the operational expense ratio for the corresponding month.

A.1.3 Interchange Income, Rewards and Fraud Expenses

Three other components of credit card profitability are also reported at the portfolio level: interchange income and rewards and fraud expenses. At the account level, these measures are likely to scale with total purchase volume rather than with average daily balances. Unfortunately, we do not observe a measure of total purchase volume at the portfolio level. While there is some heterogeneity in interchange fees, average interchange income for the issuing bank is roughly 2% of overall volume (GAO, 2009). Hence, we assess interchange income at the account level to be 2% of purchase volume. The portfolio-level data show that expenditures for rewards and fraud make up about 70% of interchange income (see the bottom panel of Figure A.I). Therefore, we assess reward and fraud expenses at the account level to be $0.7 \times 2\% = 1.4\%$ of purchase volume. To validate the approach of choosing interchange income as a constant fraction of purchase volume, we conduct the following analysis: First, we use the account-level data to calculate, for every month, the ratio of purchase volume to average daily balances (see top panel of Figure A.II). Next, we combine this ratio with the portfolio-level data to impute a total purchase volume for the entire credit card portfolio. Finally, we construct the ratio of interchange income to this imputed purchase volume at the portfolio level (see bottom panel of Figure A.II). The ratio is constant at 2% over the entire sample period.

A.1.4 Return on Equity

In Section III.B we discuss the profits realized by credit card lenders in the pre-CARD Act period, estimating that credit cards generated a net profit of 1.6% of ADB.[1] After adjusting for the average tax rate for U.S. commercial banks of 32% (Lee and Rose, 2010), this translates into a Return on Assets of 1.1%, where Return on Assets (ROA) $= \frac{\text{Earnings}}{\text{Assets}}$. This is very high relative to measures of average industry profitability. The top panel of Appendix Figure A.III shows total U.S. commercial banking sector ROA over the 2000 to 2013 period. Average ROA is 0.2% during the pre-CARD Act period, and 1% over the entire period. This implies an ROA for the credit card portfolio of about five times the industry average during the pre-CARD Act period. The bottom panel of Appendix Figure A.III shows the leverage of the U.S. commercial banking sector. Given an ROA of over 1% and average leverage of about 10, this suggests a return on equity (ROE) for credit card lending of about 10%.

B Econometric Model

We estimate the parameters of the econometric model on data collapsed to groups that represent the full interaction of the categorical variables in the data. This means, in practice, that we estimate the model on data collapsed to means for each bank $\times$ product type $\times$ FICO score group $\times$ month. A product type is defined as the interaction of a consumer card indicator and whether the card is co-branded, oil and gas, affinity, student, or "other." FICO score groups are < 620, 620-659, 660-719, 720-759, 760-799, and ≥ 800. Let g denote these groups. Using this subscript, we can write the difference-in-differences specification (Equation 2 in the main text) as

$$y_{igt} = \alpha_t + \alpha_C \mathbb{1}_{g\in\text{Consumer}} + \beta_1 \, \mathbb{1}_{g\in\text{Consumer}} \cdot \mathbb{1}_{t\in\text{Phase 2}} + \beta_2 \, \mathbb{1}_{g\in\text{Consumer}} \cdot \mathbb{1}_{t\in\text{Phase 3}} + X'_{gt}\alpha_X + \epsilon_{igt},$$

where the g subscripts on $\mathbb{1}_{g\in\text{Consumer}}$ and X_{gt} indicate these variables vary, respectively, at the group and group $\times$ month level. This specification is identical to the hierarchical regression model:

[1] Our measure of net profits subtracts out financing costs and other expenses. The other adjustment one might want to make is to include some of the purchase volume that gets repaid at the end of the period. This value would not show up in ADB, but would still be part of the bank's assets during the month. Table II shows that this adjustment would not make a large quantitative difference. An upper bound on the assets we would miss is the total purchase volume divided by 2 (i.e., assuming that it gets built up evenly throughout the month). Since the number presented in Table II is annualized, including purchase volume in the total assets would add about $75 or about 6% to total assets. This is an upper bound on the total amount, since the fraction of purchase volume that is not repaid at the end of the month might already be included in average daily balances.

$$y_{igt} = \lambda_{gt} + \nu_{igt}$$
$$\lambda_{gt} = \alpha_t + \alpha_C \mathbb{1}_{g\in\text{Consumer}} + \beta_1\ \mathbb{1}_{g\in\text{Consumer}} \cdot \mathbb{1}_{t\in\text{Phase 2}} + \beta_2\ \mathbb{1}_{g\in\text{Consumer}} \cdot \mathbb{1}_{t\in\text{Phase 3}} + X'_{gt}\alpha_X + \mu_{gt},$$

where the first equation is a regression of the account-level outcomes on group $\times$ month fixed effects, and the second equation is a difference-in-differences specification with these fixed effects as the dependent variable. The account-level error is defined as the sum of errors from the hierarchical model: $\epsilon_{igt} = \mu_{gt} + \nu_{igt}$. We can estimate the group $\times$ month fixed effects $\hat{\lambda}_{gt}$ by collapsing the data to the group level. Given these estimates, we can recover the coefficient of interest with a difference-in-differences regression with these groups fixed effects as the dependent variable:

$$\hat{\lambda}_{gt} = \alpha_t + \alpha_C \mathbb{1}_{g\in\text{Consumer}} + \beta_1\ \mathbb{1}_{g\in\text{Consumer}} \cdot \mathbb{1}_{t\in\text{Phase 2}} + \beta_2\ \mathbb{1}_{g\in\text{Consumer}} \cdot \mathbb{1}_{t\in\text{Phase 3}} + X'_{gt}\alpha_X + \mu_{gt} + \bar{\nu}_{gt}.$$

This regression has two errors terms: the error μ_{gt} that represents unobserved determinants of the outcome at the group $\times$ month level and the error $\bar{\nu}_{gt} = \hat{\lambda}_{gt} - \lambda_{gt}$ in the prediction of the fixed effect. In the regressions, we weight the group-level observations to allow us to interpret the resulting estimates as aggregate effects. In particular, when the dependent variable is denominated as an annualized percentage of ADB (e.g., over limit fees as an annualized percentage of ADB), we weight by total ADB in each group. For other dependent variables (e.g., credit limits), we weight by the number of accounts in each group.

C Theoretical Model

In this appendix we present a model to formalize the intuition discussed in Section VI. The model shows that the extent to which an increase in fee limits is offset and credit supply is adjusted is determined by (i) the degree of competition in the market and (ii) the salience of the regulated fee.

C.1 Setting

Consider a setting in which n symmetric firms compete to offer a credit card with a salient price p_1 (e.g., interest rate) and a potentially non-salient price p_2 (e.g., over limit fee).[2] Since firms are identical, they charge the same prices in equilibrium. Aggregate demand is given by the function

[2] See Stango and Zinman (2014) and Bar-Gill and Bubb (2012) for discussions of the salience of credit card fees.

$q(p_1 + \psi p_2)$, where $\psi \in [0,1]$ parameterizes the degree of salience of p_2.[3] A value of $\psi = 1$ indicates perfect salience; a value of $\psi = 0$ indicates that consumers are completely oblivious to p_2. Following Heidhues, Kőszegi and Murooka (2012), we assume there is a maximum $\bar{p}_2$ that is determined by regulation or some other factor.[4]

Firms have identical costs structures, which include both the cost of financing consumer lending and the cost of default. Assume for now that lending to consumers has constant marginal costs c. In Appendix C.4, we show that the results are similar when we allow for marginal costs to vary, as they would in an environment with adverse or advantageous selection.

It is optimal for firms to set the potentially non-salient price p_2 to the maximum allowable amount $\bar{p}_2$.[5] Following Weyl and Fabinger (2013), we characterize the first order condition for the salient price p_1 as

$$p_1 + p_2 - c = \theta\, \mu(p_1 + \psi p_2), \tag{1}$$

in which the markup of price over marginal cost is set equal to the product of a market competitiveness parameter $\theta \in [0,1]$, which indexes the degree of competition in the market (see Bresnahan, 1989), and an absolute markup function $\mu(p_1 + \psi p_2) \equiv -\frac{q}{q'}$, which is the markup that would be charged by a monopolist.[6]

The specification is flexible and nests a number of standard cases. Perfect competition is given by $\theta = 0$ and simplifies the first order condition to the standard "price equals marginal cost" condition $p_1 + p_2 = c$. Monopoly is given by $\theta = 1$ and simplifies the equation to the Lerner Index for optimal pricing $\frac{p_1+p_2-c}{p_1} = \frac{1}{\varepsilon_{p_1}}$, where ε_{p_1} is the aggregate elasticity of demand. Cournot competition is given by $\theta = 1/n$, where n is the number of firms.[7]

[3] Our use of the term salience follows Chetty, Looney and Kroft (2009) to characterize the reduced "visibility" of the price. We are agnostic over whether this limited salience arises from a behavioral micro-foundation (e.g., inattention, myopia) or a non-behavioral model of consumer behavior (e.g., higher search costs on this dimension).

[4] Alternatively, one could specify demand as a function of $q(p_1 + \psi(p_2))$, where $\psi(\cdot)$ is increasing and convex and has the property $\psi'(\bar{p}_2) = 1$. This would result in the firm setting $p_2 = \bar{p}_2$ in equilibrium.

[5] To see this, suppose a firm sets a $p_2 < \bar{p}_2$. The firm can increase profits by decreasing the salient price by ψdp_2 and increasing the non-salient price by dp_2. This pricing change has no effect on demand because $q\left(p_1 - \psi dp_2 + \psi(p_2 + dp_2)\right) = q(p_1 + \psi p_2)$ but raises total profits by $(1-\psi)\, dp_2\, q(p_1 + \psi p_2) > 0$. This means that $p_2 < \bar{p}_2$ cannot be an equilibrium. If p_2 is perfectly salient ($\psi = 1$), the equilibrium is described by a single price $p^* \equiv p_1 + p_2$ and firms are indifferent between all combinations of p_1 and p_2 that sum to this p^*, including the combination with $p_2 = \bar{p}_2$.

[6] The second order condition for p_1 is $\theta\, \mu' < 1$. We assume that at the optimal price this condition is satisfied.

[7] See Weyl and Fabinger (2013) and Mahoney and Weyl (2013) for discussions of the micro-foundations of this specification.

C.2 *Pricing Offset*

Consider a regulation that decreases the maximum allowable price $\bar{p}_2$. We want to know how much of the decline in p_2 is offset by an increase in p_1. For small changes in p_2, this offset is given by $\omega \equiv -\frac{dp_1}{dp_2}$. We will say there is full offset if $\omega = 1$ and no offset if $\omega = 0$.

Assume that θ and ψ are invariant to the price. Totally differentiating the first order conditions (Equation 1) with respect to p_2 and rearranging yields

$$\omega = \frac{1 - \psi\,\theta\,\mu'}{1 - \theta\,\mu'}, \tag{2}$$

where we have suppressed the arguments of μ for notational simplicity. To gain intuition for the offset formula, consider two special cases.

Special Case 1. *(Perfect Competition) If there is perfect competition ($\theta = 0$), then a limit on p_2 will be fully offset by an increase in p_1 ($\omega = 1$).*

Since competition drives price to marginal cost, any decrease in p_2 must be fully offset by an increase in p_1 to maintain zero markup in equilibrium.[8]

Special Case 2. *(Perfect Salience) If p_2 is perfectly salient ($\psi = 1$), then a limit on p_2 will be fully offset by an increase in p_1 ($\omega = 1$).*

If p_2 is perfectly salient, consumers view both prices as equivalent and firms can maintain their desired level of demand by increasing p_1 one-for-one with the decline in p_2.

Intuitively, the offset can be less than one-for-one when there is both imperfect competition ($\theta > 0$) and imperfect salience ($\psi < 1$). Taking derivatives of Equation 2 with respect to θ and ψ yields the following proposition:

Proposition 1. *(Offset) The offset is converging toward full ($\omega \to 1$) as (i) the market becomes more competitive ($\theta \to 0$) and (ii) p_2 becomes more salient ($\psi \to 1$).*

The offset is converging from below for many standard parameterizations of demand, but can also converge from above for some parameterizations. Technically, the offset converges from below when $\mu' < 0$ or equivalently if log demand is concave, since $(\log q)'' = \mu'/\mu^2 < 0 \iff \mu' < 0$.[9]

[8] In our model, perfect competition implies that price equals marginal costs. However, Parlour and Rajan (2001) show that in more complex settings, even credit markets with free entry can sustain positive profits for lenders.

[9] Fabinger and Weyl (2013) prove that $\mu' < 0$ if demand is linear or if it is based on an underlying willingness-to-pay distribution that is normal, logistic, Type I Extreme Value (logit), Laplace, Type III Extreme Value, or Weibull or Gamma with shape parameter $\alpha > 1$. They show that $\mu' > 0$ if demand is based on a willingness-to-pay distribution that is Pareto (constant elasticity), Type II Extreme Value, or Weibull or Gamma with shape parameter $\alpha < 1$. They show that μ switches from $\mu' < 0$ to $\mu' > 0$ for a log-normal distribution of willingness-to-pay.

C.3 *Volume Response*

The model also provides guidance on how the equilibrium volume of credit will respond to a regulation that decreases the maximum allowable price $\bar{p}_2$. For small changes in p_2, this volume effect is given by $\nu \equiv -\frac{dq}{dp_2}$. Totally differentiating q with respect to p_2 and using the identities $\omega = -\frac{dp_1}{dp_2}$ and $\frac{\partial q}{\partial p_1} = \psi \frac{\partial q}{\partial p_2}$ to simplify yields:

$$\nu = \frac{\partial q}{\partial p_1}(\omega - \psi). \tag{3}$$

The quantity response is largest (in absolute value) when p_2 is non-salient ($\psi = 0$) and markets are competitive ($\theta = 0$) because firms fully offset the p_2 decline ($\omega = 1$, see Special Case 1) but consumers only observe the increase in p_1 and reduce their demand accordingly. There is no quantity response when p_2 is perfectly salient ($\psi = 1$) because even though firms fully offset the p_2 decline ($\omega = 1$, see Special Case 2), consumers observe this one-for-one tradeoff between p_2 and p_1 and do not change their demand. More broadly, the volume response is increasing in the size of the offset (ω) and decreasing in the salience of the non-salient price (ψ).

C.4 *Fee Offset with Selection*

The composition of the borrower pool may not be invariant to the prices charged, and changing the price might attract either higher or lower marginal cost consumers (Agarwal et al., 2014*a*).[10] To allow for such adverse or advantageous selection, we allow aggregate marginal costs $c'(q)$ to depend on aggregate demand q. Adverse selection at the industry level is indicated by decreasing aggregate marginal costs: $c''(q) < 0$; advantageous selection is indicated by increasing aggregate marginal costs: $c''(q) > 0$.

When a single firm lowers its price, it attracts consumers that are new to the market and consumers who are already purchasing the product from competing firms. The share of consumers firm i captures from its competitors is given by the aggregate diversion ratio: $A = -\frac{\sum_{j \neq i} \partial q_j / \partial p_i}{\partial q_i / \partial p_j}$, the sum of consumers lost by firms $j \neq i$ divided by the consumers gained by firm i.[11]

We assume that consumers acquired from competitors are not selected and have costs equal to industry average cost: $\frac{c(q)}{q}$. Marginal costs for a single firm $c_i'(q_i)$ are the weighted sum of marginal

[10] Similarly, changing the price might have a direct impact on costs. For example, if high prices increase debt levels and thereby increases the probability of default.

[11] We thank Glen Weyl for suggesting this approach to modeling selection.

costs for consumers that are new to the market and marginal costs for consumers that are attracted from other firms:

$$c_i'(q_i) = (1-A)c'(q) + A\frac{c(q)}{q}. \tag{4}$$

It is convenient to characterize the demand curve faced by a single firm in terms of aggregate demand and the aggregate diversion ratio:

$$1 - A = 1 - \frac{\sum_{j\neq i} \partial q_j/\partial p_i}{\partial q_i/\partial p_i} = \frac{\partial q_i/\partial p_i - \sum_{j\neq i} \partial q_j/\partial p_i}{\partial q_i/\partial p_i} = \frac{q'}{q_i'} \quad \Longleftrightarrow \quad q_i' = \frac{q'}{1-A}, \tag{5}$$

where q' is the derivative of aggregate demand with respect to the price p_1 of a single firm i. The first order condition for p_1 is given by

$$p_1 + p_2 - c_i'(q_i) = \theta\,\mu(p_1 + \psi p_2), \tag{6}$$

with the conduct parameter $\theta \in [0,1]$ and markup term $\mu(p_1 + \psi p_2)$ as previously defined. The second order condition for p_1 is $\theta\,\mu' + c''\,q' < 1$. We assume that at the optimal price this condition is satisfied. For small changes in p_2, we can calculate pass-through by totally differentiating the first order condition:

$$\frac{dp_1}{dp_2} + 1 - c_i''(q_i)\,q_i' \left[\frac{dp_1}{dp_2} + \psi\right] = \theta\,\mu'(p_1 + \psi p_2) \left[\frac{dp_1}{dp_2} + \psi\right]. \tag{7}$$

Substituting $c_i'' = (1-A)c''$ and $q_i' = \frac{q'}{1-A}$ and rearranging gives us the pass-through formula:

$$\omega = \frac{1 - \psi\,[\,\theta\,\mu' + \,c''\,q']}{1 - [\theta\,\mu' + c''\,q']}, \tag{8}$$

where we have suppressed the arguments of c, q, and μ.

The offset ω is increasing in the term $c''\,q'$. With downward sloping demand $q' < 0$, this means that the offset is relatively larger when there is adverse selection ($c'' < 0$) and relatively smaller when there is advantageous selection ($c'' > 0$). The reason the offset is larger with adverse selection is that a higher p_1 brings in higher marginal cost consumers, requiring a further increase in price.

Under what conditions is the offset less than full? The second order condition $\theta\,\mu' + \,c''\,q' < 1$

restricts the numerator and denominator to be positive. For $\psi \in (0,1)$, it follows that

$$\omega < 1 \iff \theta\,\mu' + c''\,q' < 0. \tag{9}$$

Under what conditions is the offset increasing in competition? Differentiating the pass-through formula yields

$$\frac{d\omega}{d\theta} = \frac{[1-\theta\,\mu' - c''\,q']\,[-\psi\,\mu'] - [1-\psi\,\theta\,\mu' - \psi\,c''\,q']\,[-\mu']}{[1-\theta\,\mu' - c''\,q']^2}, \tag{10}$$

which simplifies to

$$\frac{d\omega}{d\theta} = \frac{\mu'\,[1-\psi]}{[1-\theta\,\mu' - c''\,q']^2}. \tag{11}$$

Since the denominator is always positive, for $\psi \in (0,1)$ we have

$$\frac{d\omega}{d\theta} < 0 \iff \mu' < 0, \tag{12}$$

where recall that increasing competition is indicated by a lower value of θ.

Under what conditions is the offset increasing in salience? Differentiating the pass-through formula gives us:

$$\frac{d\omega}{d\psi} = -\frac{[\theta\,\mu' + c''\,q']}{1-[\theta\,\mu' + c''\,q']}. \tag{13}$$

Since $\theta\,\mu' + c''\,q' < 0$ is implied by the second order condition, it follows that

$$\frac{d\omega}{d\psi} > 0 \iff \theta\,\mu' + c''\,q' < 0. \tag{14}$$

D Ancillary Evidence from Pass-Through

The theoretical model in Appendix C allows us to establish a link between the offset of a reduction in the non-salient price and the pass-through of an increase in marginal costs, which we can use to test the consistency of our theoretical and empirical results.

Let $\rho \equiv \frac{dp_1}{dc}$ denote the pass-through of a increase in marginal costs. Differentiating the first order conditions of the model without selection (Equation 1) with respect to c yields $\rho = \frac{1}{1-\theta\,\mu'}$. We can then write the offset as a function of the pass-through rate:

$$\omega = \rho + \psi\,(1-\rho)\,. \tag{15}$$

When p_2 is non-salient ($\psi = 0$), the offset is equal to the pass-through rate ($\omega = \rho$). When p_2 is fully observed ($\psi = 1$), the offset is full ($\omega = 1$). Intuitively, banks will pass through the decrease in fee revenue by at least as much as a marginal cost shock, and by more if the change in fees is salient.

This equation is useful because it places restrictions on the relationship between the offset ω, pass-through rate ρ, and salience parameter ψ. In a related paper, Agarwal et al. (2014*b*) argue ρ and ψ are "sufficient statistics" that can be used to estimate the consumer benefits from regulating hidden fees in a wide range of settings, and illustrate the applicability of this approach by assessing a hypothetical regulation of airline baggage fees.

In this context, we can use this equation to provide ancillary evidence for our estimate of the offset. Ausubel (1991) examines the time-series correlation between the cost of funds and interest rates in the credit card market. He finds that interest rates are extremely sticky, with credit card issuers passing through essentially zero of the large changes in the cost of funds over the 1980s time period. Similarly, there is significant evidence that late fees and over limit fees have only limited salience to consumers (Sunstein, 2006; Bar-Gill and Warren, 2008; Mullainathan, Barr and Shafir, 2009; Stango and Zinman, 2014). If we assume, as a starting point, that banks pass through $\rho = 0.1$ of changes in the cost of funds and a salience parameter of $\psi = 0.1$, the model indicates that every dollar in fee reduction, credit card issuers will increase prices by about 19 cents ($\omega = \rho + \psi\,[1-\rho] = 0.1 + 0.1[1-0.1] = 0.19$), a value that is squarely within the confidence interval of our offset estimate.

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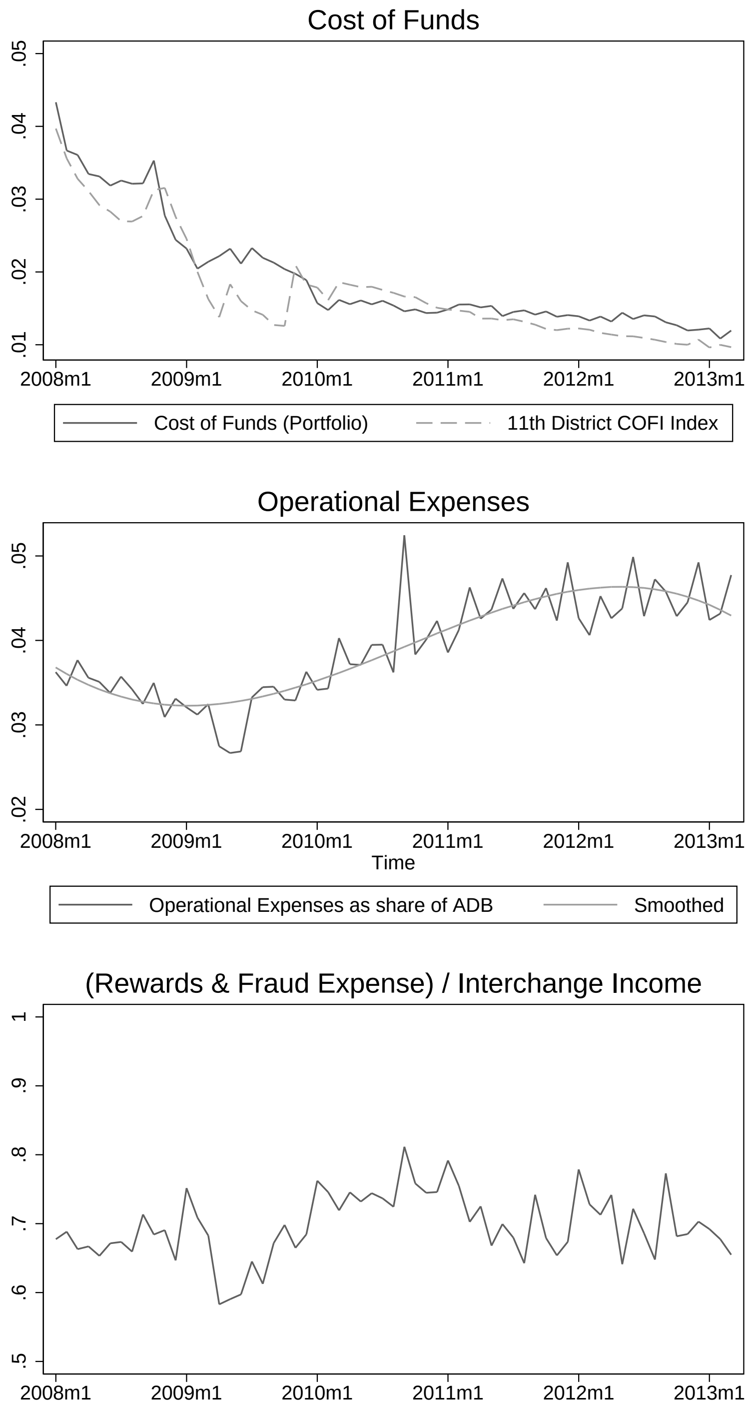
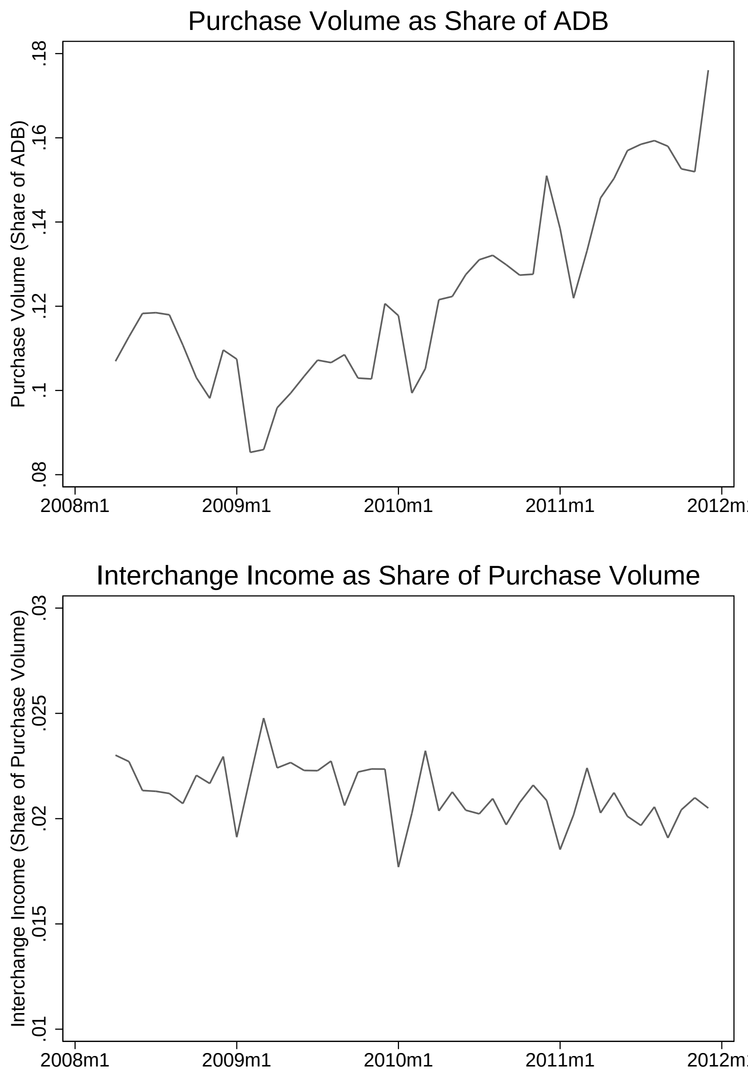
Figure A.I: Portfolio Data



Note: Figure shows plots of cost components by month. The top panel shows the cost of funds, calculated as the annualized interest expense ("total interest expense accrued for the month to fund credit card receivables") as a share of average daily managed receivables for that month. It also shows the 11th District Cost of Funds Index (COFI). The middle panel shows the share of annualized operational expenses (including marketing and acquisition, collections, servicing, cardholder billing, processing payments, and card issuing and administration) as a share of average daily managed receivables. The bottom panel shows the share of rewards and fraud expenses as a ratio of the interchange income. These figures are constructed using the monthly general purpose credit card portfolio-level data. Numbers are averages across banks.

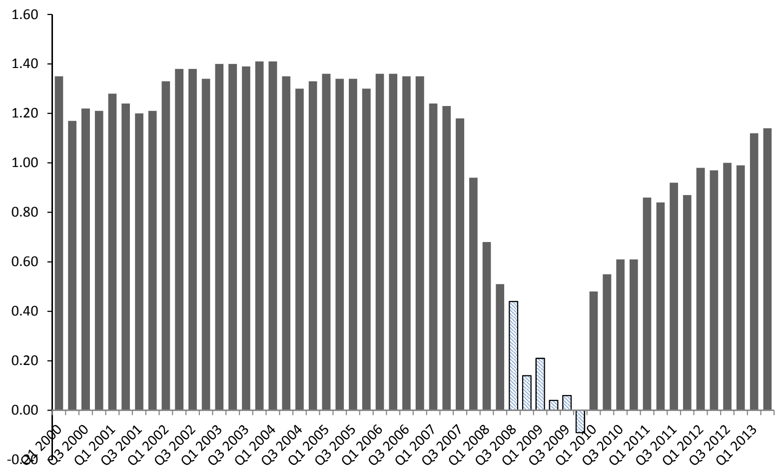
Figure A.II: Interchange Income



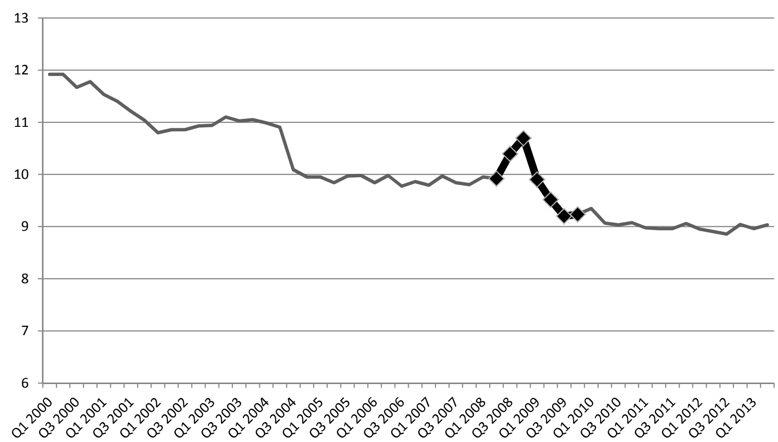
Note: Figure shows ratio of purchase volume to ADB (top panel) and ratio of interchange income to purchase volume (bottom panel). The top panel is constructed from account-level data. The bottom panel is constructed by taking the information from the top panel to scale the portfolio-level information on ADB to get a portfolio-level of measure of purchase volume. Total interchange income is also reported at the portfolio level.

Figure A.III: U.S. Commercial Banking Sector: ROA and Leverage

(A) Return on Assets (ROA)

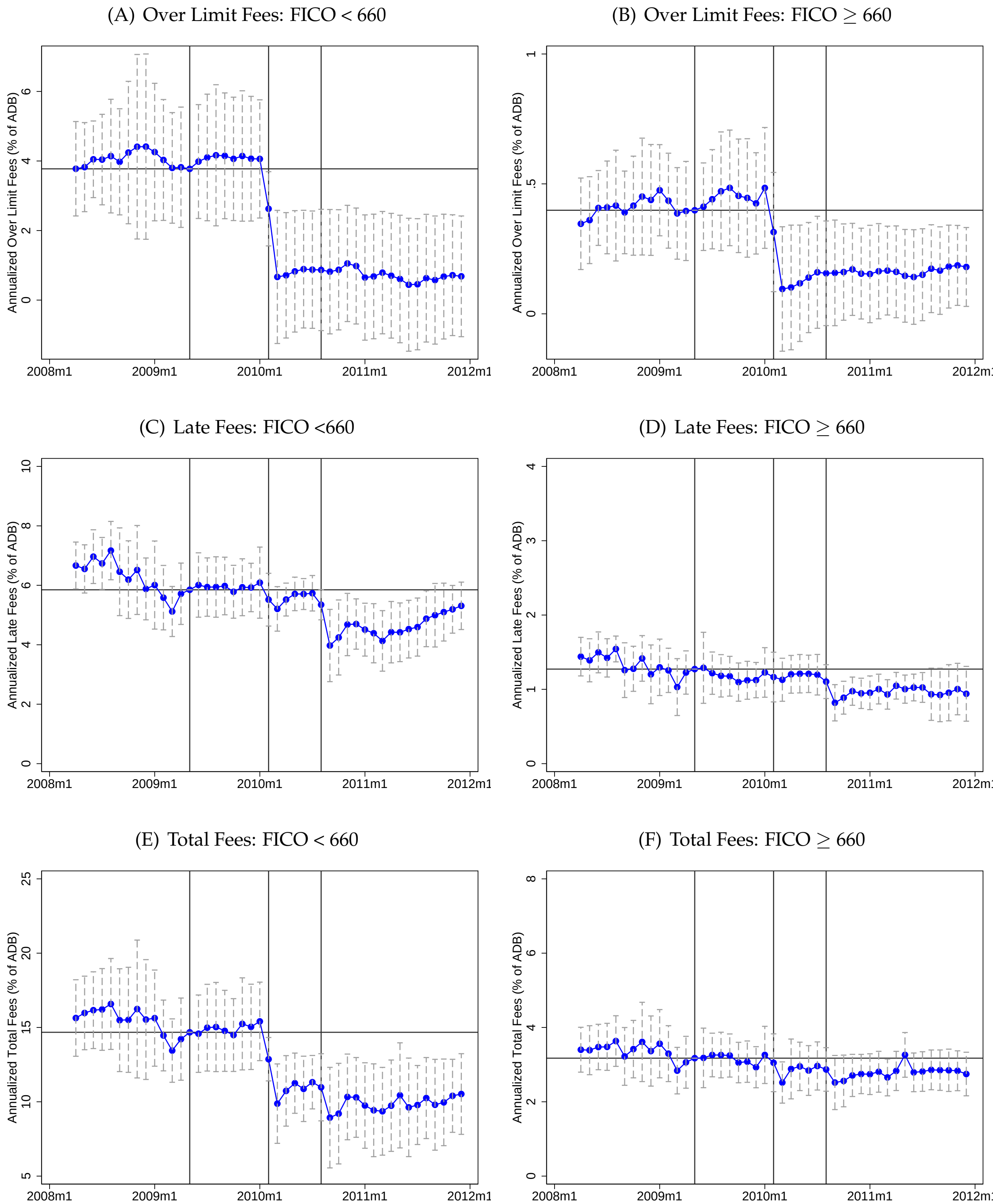


(B) Leverage



Note: Panel A shows the average Return on Assets (ROA) in percent for all insured U.S. Commercial Banks (FRED Series USROA) as reported by the Federal Financial Institutions Examination Council. Panel B reports the leverage (Total Assets / Total Equity) for all insured U.S. Commercial Banks (the inverse of FRED Series EQTA). The shaded bars in Panel A and bolded line in Panel B depict the pre-CARD Act period covered in Table II.

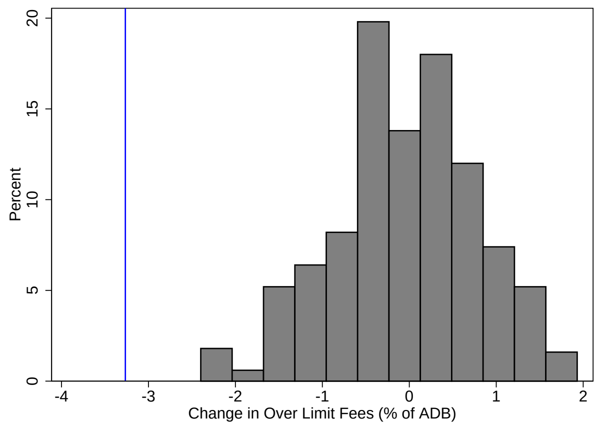
Figure A.IV: Regression Coefficients: Over Limit Fees, Late Fees, and Total Fees



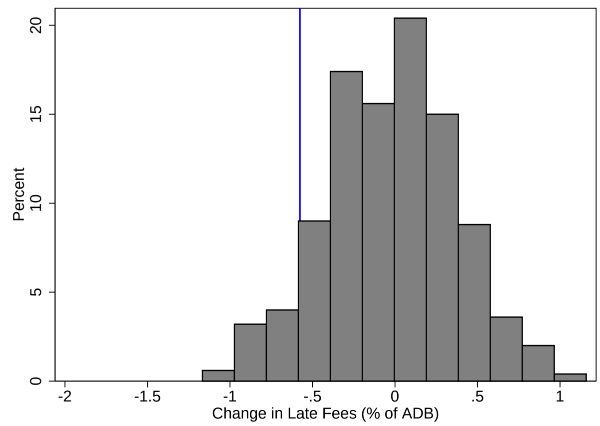
Note: Figure shows the coefficients on consumer account × month interactions from a difference-in-differences regression (Equation 2 in the main text) with over limit fees (top row), late fees (middle row) and total fees (bottom row) as an annualized percentage of ADB as the dependent variable. We normalize the coefficient on the month when the bill was signed to the pre-CARD Act consumer account mean. We include fixed effects for consumer account, month, and bank × FICO score group. The sample period is April 2008 to December 2011. Vertical lines are plotted in May 2009, February 2010, and August 2010, the date when the bill was signed and the two key implementation dates of the CARD Act, respectively. Standard errors are clustered at the bank × product type level, with capped bars showing 95% confidence intervals.

Figure A.V: Fees: Permutation Tests

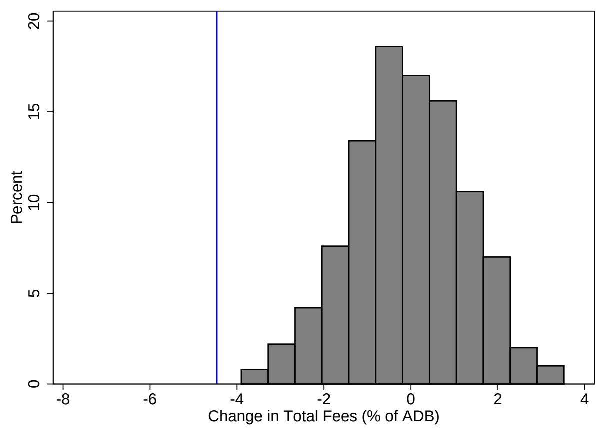
(A) Over Limit Fees



(B) Late Fees



(C) Total Fees

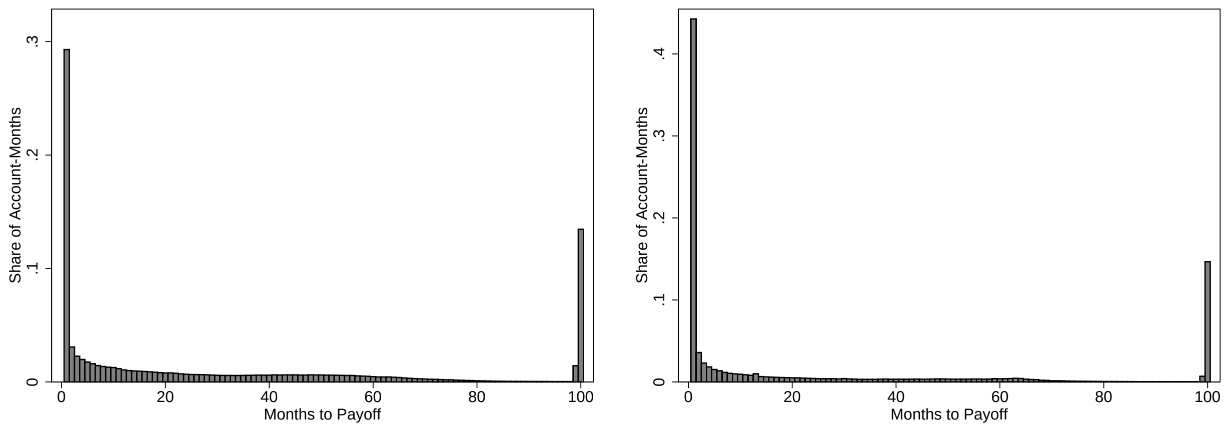


Note: Figure shows results of permutation tests where we compare our estimate of the actual CARD Act to the distribution of placebo estimates derived from 1,000 samples where "treatment" is randomly assigned. Panel A examines over limit fees, and compares the actual Phase 2 estimate (solid line) to a distribution of placebo Phase 2 estimates. Panels B and C examine late fees and total fees, and compare the actual Phase 3 estimates (solid lines) to distributions of placebo Phase 3 estimates. See Section IV for additional details.

Figure A.VI: Distribution of Months-to-Payoff (T) in Pre-CARD Act Period

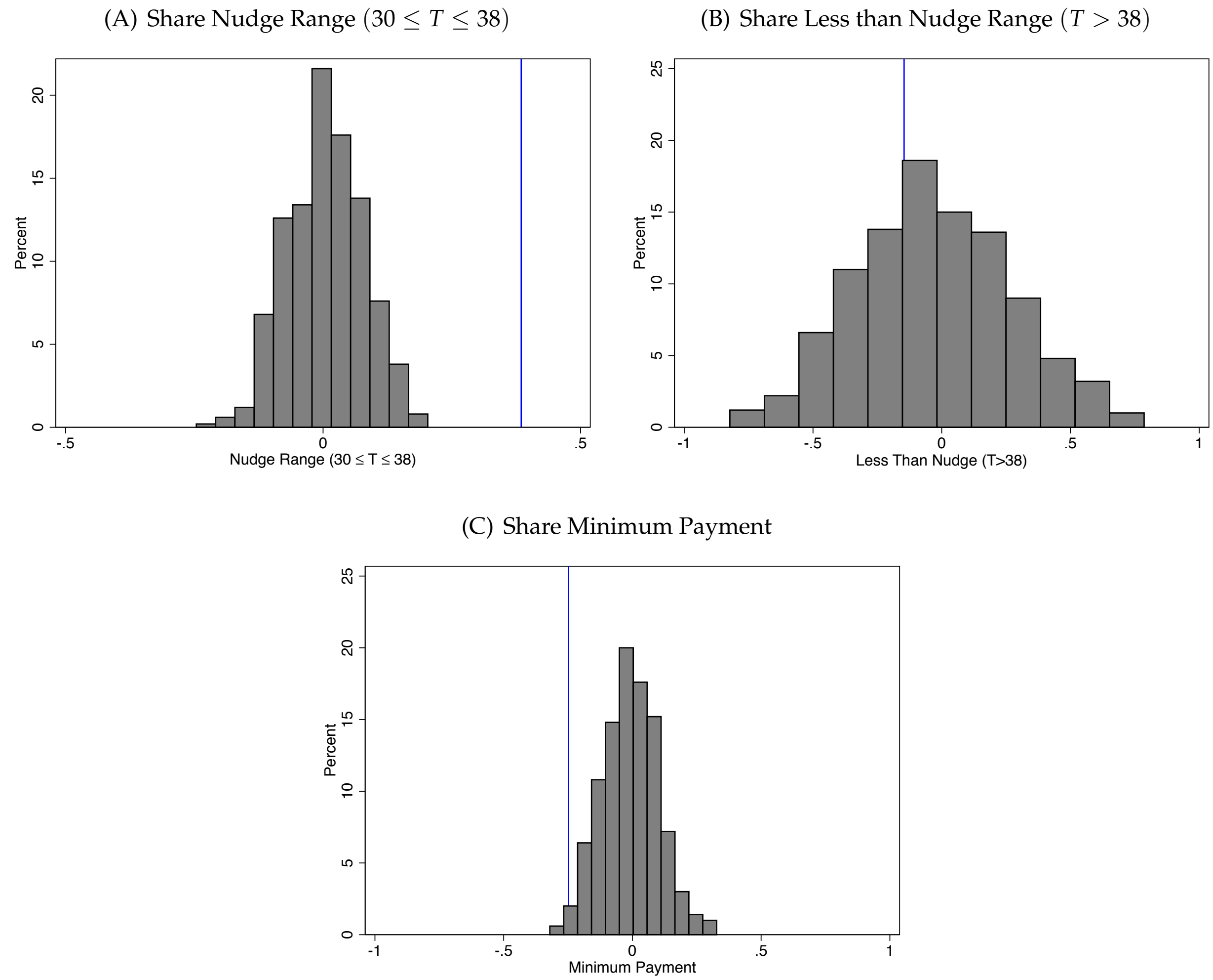
(A) Consumer Credit Cards

(B) Small Business Credit Cards



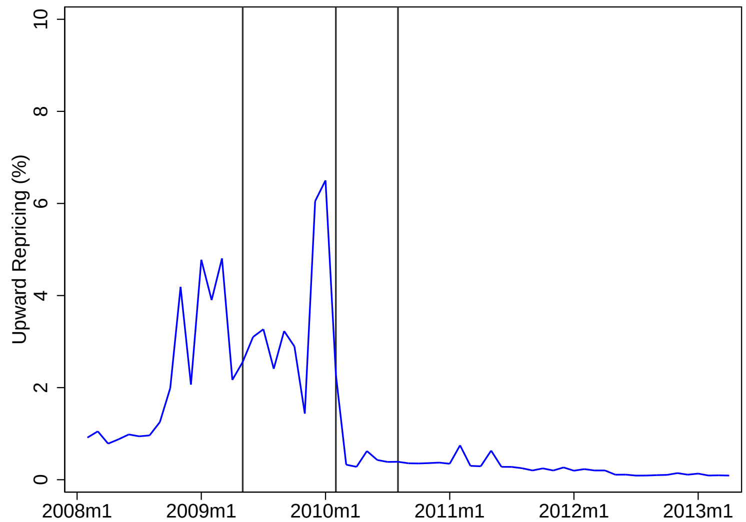
Note: Figure shows histograms of months-to-payoff (T) in the year preceding the CARD Act, defined as February 2009 to January 2010. Months-to-payoff (T) is the number of months it would take to pay off the cycle-ending balance if the account holder makes constant payments and makes no new purchases, and is calculated using Equation 3 in the main text. The variable T is top-coded at 99 months with $T = 100$ denoting account holders that make no payment. Panel A shows the distribution for consumer credit cards. Panel B shows the distribution for small business credit cards.

Figure A.VII: Payoff Behavior: Permutation Tests



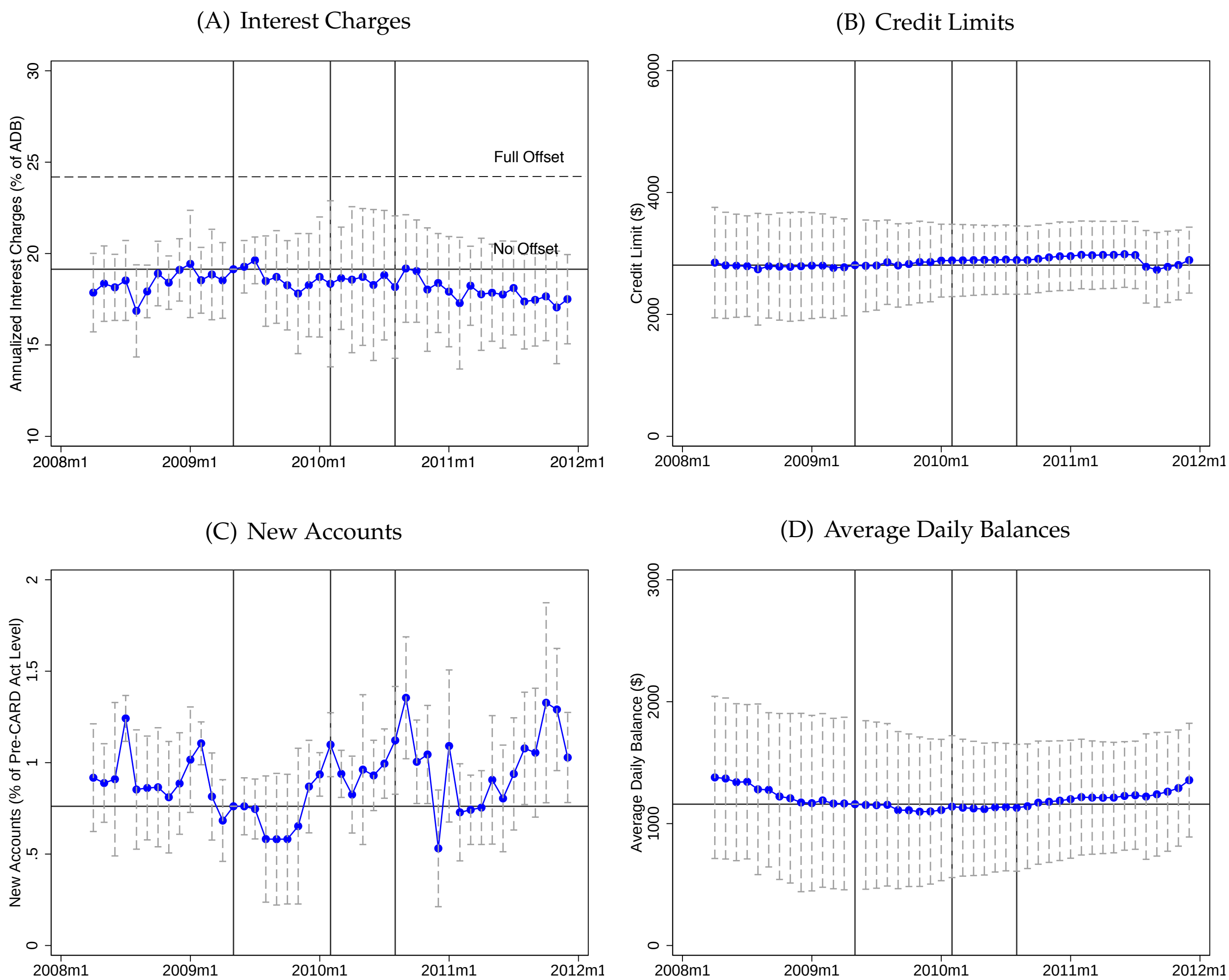
Note: Figure shows results of permutation tests where we compare our estimate of the actual CARD Act to the distribution of placebo estimates derived from 1,000 samples where "treatment" is randomly assigned. Panel A examines the share of accounts making a payment in the nudge range $(30 \leq T \leq 38)$, Panel B the share of accounts making payments smaller than the nudge range $(T > 38)$, and Panel C examines the share of accounts making exactly the minimum payment. All graphs compare the actual Phase 2 estimate (solid line) to a distribution of placebo Phase 2 estimates. See Section IV for additional details.

Figure A.VIII: Upward Repricing



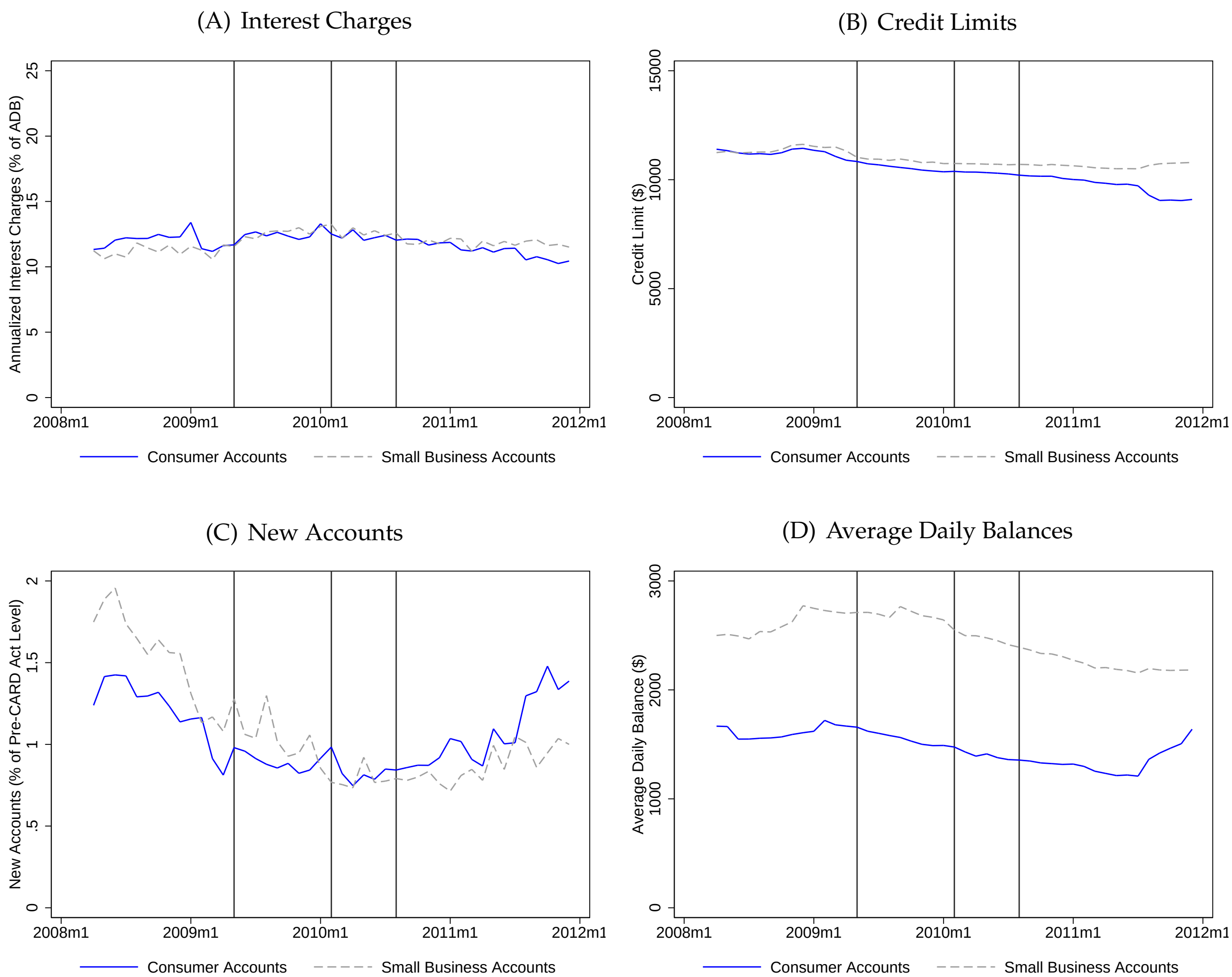
Note: Figure shows the share of consumer accounts with upward repricing over time. Following Consumer Financial Protection Bureau (2013), upward repricing is defined as an APR increases of at least 1 percentage point from a base of at least 10% in the previous month, to exclude increases that occur at the end of introductory rate periods. The sample period is January 2008 to April 2013. Vertical lines are plotted in May 2009, February 2010, and August 2010, the date when the bill was signed and the two key implementation dates of the CARD Act, respectively.

Figure A.IX: Regression Coefficients: Interest Charges and Credit Volume: FICO < 660



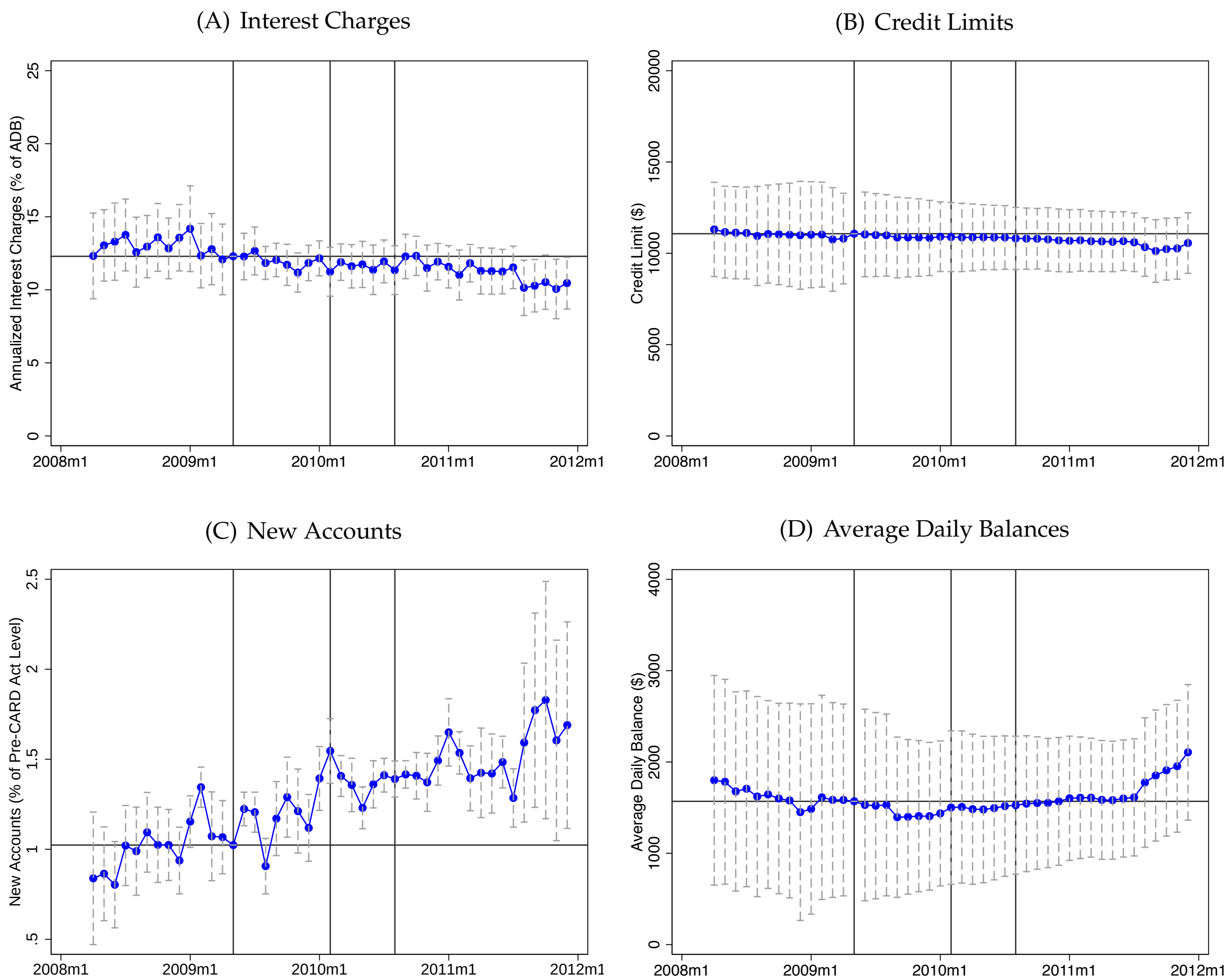
Note: Figures show the coefficients on consumer account $\times$ month interactions from a difference-in-differences regression (Equation 2 in the main text). The dependent variables are interest charges as an annualized percentage of ADB (Panel A), credit limits (Panel B), new accounts measured as a percentage of average total pre-CARD Act number of accounts (Panel C), and average daily balances (Panel D). All panels focus on account holders with a FICO score below 660 at account origination. We normalize the coefficient on the month when the bill was signed to the pre-CARD Act consumer account mean. We include fixed effects for consumer account, month, and bank $\times$ FICO score group. The sample period is April 2008 to December 2011. Vertical lines are plotted in May 2009, February 2010, and August 2010, the date when the bill was signed and the two key implementation dates of the CARD Act, respectively. Standard errors are clustered at the bank $\times$ product type level, with capped bars showing 95% confidence intervals.

Figure A.X: Interest Charges and Credit Volume: FICO $\geq$ 660



Note: Panel A shows interest charges as an annualized percentage of ADB. Panel B shows credit limits. Panel C shows new accounts measured as a percentage of average total pre-CARD Act number of accounts. Panel D shows average daily balances. All panels focus on account holders with a FICO score of at least 660 at account origination, and display monthly averages for consumer and small business credit cards. The sample period is April 2008 to December 2011. Vertical lines are plotted in May 2009, February 2010, and August 2010, the date when the bill was signed and the two key implementation dates of the CARD Act, respectively.

Figure A.XI: Regression Coefficients: Interest Charges and Credit Volume: FICO $\geq$ 660



Note: Figures show the coefficients on consumer account × month interactions from a difference-in-differences regression (Equation 2 in the main text). The dependent variables are interest charges as an annualized percentage of ADB (Panel A), credit limits (Panel B), new accounts measured as a percentage of average total pre-CARD Act number of accounts (Panel C), and average daily balances (Panel D). All panels focus on account holders with a FICO score of at least 660 at account origination. We normalize the coefficient on the month when the bill was signed to the pre-CARD Act consumer account mean. We include fixed effects for consumer account, month, and bank × FICO score group. The sample period is April 2008 to December 2011. Vertical lines are plotted in May 2009, February 2010, and August 2010, the date when the bill was signed and the two key implementation dates of the CARD Act, respectively. Standard errors are clustered at the bank × product type level, with capped bars showing 95% confidence intervals.

Table A.I: Sample Description

Quarter	Banks	Reporting Accounts	
		Consumer	Small Business
2008			
Q2	8	146,791,168	7,422,173
Q3	8	149,206,816	7,520,410
Q4	8	150,897,312	7,509,002
2009			
Q1	8	156,140,112	7,441,551
Q2	8	153,784,576	7,398,919
Q3	8	151,710,160	7,248,530
Q4	8	150,692,000	7,037,414
2010			
Q1	8	148,839,584	6,945,099
Q2	8	148,081,888	6,874,883
Q3	8	147,366,704	6,586,668
Q4	8	145,080,128	6,432,164
2011			
Q1	8	145,119,552	6,382,301
Q2	8	145,631,632	6,366,402
Q3	8	147,312,352	6,499,508
Q4	8	137,829,936	6,573,073

Note: Table shows the number of consumer and small business accounts by quarter for the sample period, defined as Q2 2008 to Q4 2011.

Table A.II: Interest Charges for New and High FICO Score Accounts: Difference-in-Differences Regressions

	Dependent Variable: Interest Charges (% of ADB)							
	FICO < 660				FICO ≥ 660			
	All Accounts		New Accounts		All Accounts		New Accounts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consumer X Anticipation	0.25	0.29	-2.83	-1.25	-0.86	-1.02	-0.47	-0.57
	(1.40)	(1.40)	(2.03)	(1.40)	(1.21)	(1.14)	(0.80)	(0.64)
	[0.86]	[0.84]	[0.17]	[0.38]	[0.48]	[0.38]	[0.56]	[0.38]
Consumer X Phase 2	0.22	0.17	-4.50*	-3.19**	-0.97	-1.32	-1.79	-1.51*
	(2.31)	(2.26)	(2.22)	(1.13)	(2.02)	(1.79)	(1.14)	(0.86)
	[0.92]	[0.94]	[0.05]	[0.01]	[0.63]	[0.46]	[0.12]	[0.09]
Consumer X Phase 3	-0.34	-0.48	1.25	0.17	-1.31	-1.82	-1.70*	-1.97**
	(2.03)	(1.89)	(3.10)	(1.75)	(2.00)	(1.72)	(0.81)	(0.71)
	[0.87]	[0.80]	[0.69]	[0.92]	[0.52]	[0.30]	[0.04]	[0.01]
Controls								
Main Effects								
Consumer Card FE	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X	X
Additional Covariates								
Bank FE X FICO Score Group FE		X		X		X		X
Pre-CARD Act, Consumer Mean	19.14	19.14	7.69	7.69	12.29	12.29	2.08	2.08
R-Squared	0.06	0.83	0.05	0.71	0.04	0.87	0.03	0.52
Number of Observations	3,447	3,447	3,447	3,447	6,986	6,986	6,986	6,986

Note: Table shows coefficients from difference-in-differences regressions that compare interest charges as an annualized percentage of ADB for consumer credit cards (treatment group) and small business cards (control group) during the different phases of the CARD Act implementation. We define new accounts as accounts in their first full month after account origination. We define the Anticipation period as the months between the passage of the bill in May 2009 and the implementation of Phase 2 in February 2010. We define Phase 2 as March 2010 to August 2010 and Phase 3 as the months after August 2010. The period prior to May 2009 is the omitted group, so the coefficients can be interpreted as the differential effect relative to outcomes prior to the passage of the CARD Act. The sample period is April 2008 to December 2011. The regressions are estimated on data aggregated to the bank $\times$ product type $\times$ FICO score group $\times$ month level, and weighted by total ADB in each group. A product type is defined as the interaction of the consumer card indicator and whether the card is co-branded, oil and gas, affinity, student, or "other." FICO score groups are $<$620, 620-659, 660-719, 720-759, 760-799, and $\geq$ 800. Standard errors clustered by bank $\times$ product type are shown in parentheses and the associated p-values are shown in brackets. There are 46 such clusters in columns 1 to 4 and 47 clusters in columns 5 to 8. Significance levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).